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Prasetyo, Judhi; De Masi, Giulia; Zakir, Raina; Alkilabi, Muhanad; Tuci, Elio; Ferrante, Eliseo

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A Bio-Inspired Spatial Defence Strategy for Collective Decision Making in Self-Organized Swarms

Judhi Prasetyo
Université de Namur, Namur, Belgium
Giulia De Masi
Technology Innovation Institute and Khalifa University
Raina Zakir
Middlesex University Dubai
Muhanad Alkilabi
Université de Namur, Namur, Belgium
Elio Tuci
University of Namur, Namur, Belgium
Eliseo Ferrante
Technology Innovation Institute, Abu Dhabi, UAE

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Abstract

In collective decision-making, individuals in a swarm reach consensus on a decision using only local interactions without any centralized control. In the context of the best-of-*n* problem - characterized by *n* discrete alternatives - it has been shown that consensus to the best option can be reached if individuals disseminate that option more than the other options. Besides being used as a mechanism to modulate positive feedback, long dissemination times could potentially also be used in an adversarial way, whereby adversarial swarms could infiltrate the system and propagate bad decisions using aggressive dissemination strategies. Motivated by the above scenario, in this paper we propose a bio-inspired defence strategy that allows the swarm to be resilient against options that can be disseminated for longer times. This strategy mainly consists in reducing the mobility of the agents that are associated to options disseminated for a shorter amount of time, allowing the swarm to converge to this option. We study the effectiveness of this strategy using two classical decision mechanisms, the voter model and the majority rule, showing that the majority rule is necessary in our setting for this strategy to work. The strategy has also been validated on a real Kilobots experiment.

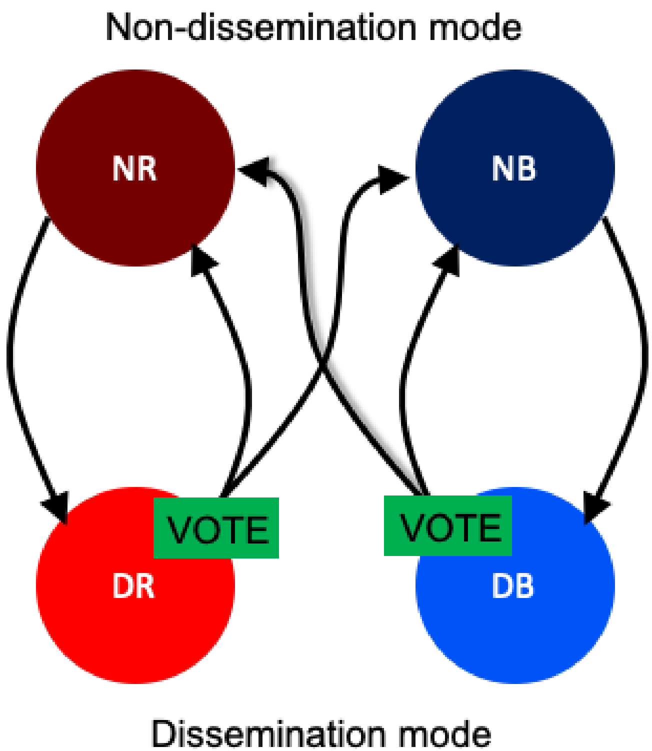

Figure 1: Probabilistic finite state machine. *NR*, *NB* , *DR* and *DB* represent the non-dissemination and dissemination states, for RED and BLUE agents respectively.

1 Introduction

In the last years, swarm robotics is getting momentum, thanks to the availability of cheaper and smaller agents, with available integrated sensors and communication devices [Hamann, 2018]. While swarms of robots that are either manually controlled or operated semi-autonomously using external sensing and/or computation are nowadays well established, the realization of fully autonomous swarms of robots, with sensing and computation realized fully on-board, is still under investigation. The field of swarm robotics defines a swarm as a potentially large group of robots that operate without any centralized or external control, but by only relying on local interaction and communication [Brambilla et al., 2013]. Swarms of robots are potentially very beneficial mostly in GPS denied environment, where the external control is prevented by the unavailability of communications or GPS.

One of the basic capability sought in a robot swarm is attainment of collective decisions [Bonabeau et al., 1999, Valentini et al., 2017]. Many other collective behaviours can be seen as an instance of collective decision making, such as deciding a com-

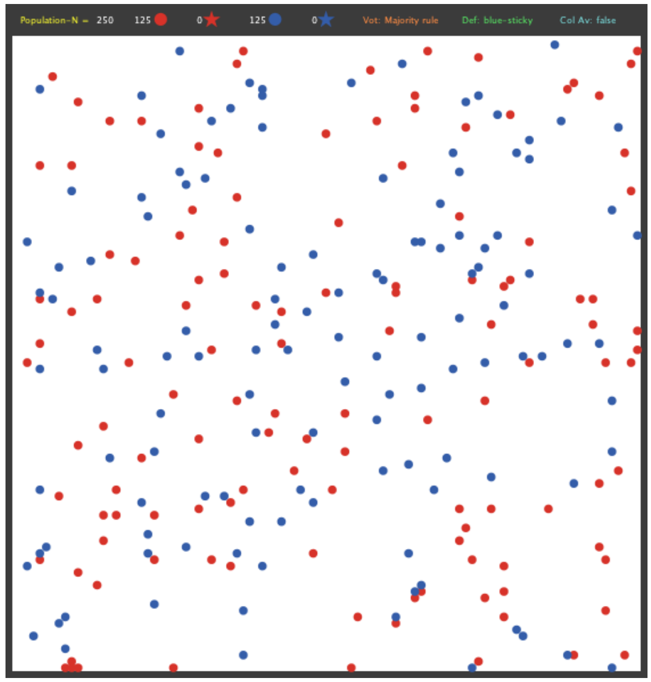

Figure 2: Screenshot of the simulation arena.

mon direction of motion [Ferrante et al., 2012], or a common location in the environment to explore at [Correll and Martinoli, 2011]. A special case of collective decision making is represented by the best-of-n problem, whereby there is a discrete number n of options and the swarm has to achieve consensus on the best of them. A perspective on the best-of-n problem can be found in [Valentini et al., 2017], whereby it is argued that two factors are key in collective decision-making: the intrinsic qualities associated to the different options [Font Llenas et al., 2018, Valentini et al., 2014, Valentini et al., 2016], or the cost associated to each option in case of asymmetrical environments [Montes de Oca et al., 2011, Scheidler et al., 2016, Brutschy et al., 2012]. In this view, the *best* option the swarm has to choose can be the one associated to the highest quality, to the lowest cost, or a compromise between these two. In general, across all those cases, the key factor determining to what option the swarm will converge is positive feedback: if robots observe, on average, more frequently one option, the swarm will more likely converge to this option. This happens because the initial symmetry (equal distribution of options) will more likely break in favour of the most frequently observed option, and subsequently this option will be even more abundant (positive feedback), thus biasing even further the consensus, and so on. This “frequency of exposure”, or modulation of positive feedback, for one option can be environment-dependent and uncontrolled (passive modulation of positive feedback) in case of asymmetric environmental cost (e.g. in tasks in which the physical path to each option differs [Montes de Oca et al., 2011]), or can be instead controlled by modulating the frequency of dissemination (active modulation of positive feedback, e.g. via communication) as a control parameter, for example by having it proportional to the quality of the option assuming it can be measured [Valentini et al., 2016]. While in general the best-of-*n* collective decision making is not adapting to sudden changes of the environments, it has been demonstrated that such adaptability can be achieved by introducing a limited number of stubborn individuals [Prasetyo et al., 2018, Masi and Ferrante, 2020].

Importantly, the mechanism for active modulation of positive feedback opens the possibility for it to be used not only as mechanism to achieve the best option, but also as a way to perform attacks by adversarial swarms wishing to manipulate the information or the mission of the focal swarm. This motivates the need to perform studies aiming at finding defence strategies whereby swarms can converge to an option even if this is less frequently disseminated compared to the one advertised by the attacker. This problem is analogous to the one encountered in other social systems, such as social media where automated bots are able to manipulate people's opinion by a massive media campaign [Ferrara, 2018]. On the application perspective, guaranteeing the safety of operations of swarms of robots outside the lab is emerging as a crucial issue [Hunt and Hauert, 2020, Reina, 2020, Jones et al., 2020]. Several approaches of defence strategy are understudy, from applications of blockchain technology [Strobel et al., 2020] to complex network analysis to evaluate the resiliency of the swarm [Liu et al., 2020].

In this paper, we propose a defence mechanism inspired by the one used by stingless bees [Nieh et al., 2005, Gastauer et al., 2011] and we demonstrate it in a multi-agent model as well as on a real kilobot proof of concept. The defence strategy is based on a reduction of the mobility pattern: the "defending" agents are allowed to simply remain at the current position, while attackers are continuously moving attempting to spread their opinion (where an opinion is the option currently chosen by an agent) within the swarm. This strategy is capable of inverting the expected final consensus, allowing the agents with lower dissemination capability to win and drive the consensus. Two voting mechanisms, used by the agents to change opinion based on neighbors opinion, are considered: the voter model, whereby agents change opinion copying a random neighbor, and the majority rule, whereby agents change opinion to the option held by the majority of a group of neighbors. The problem of designing defence mechanisms for self-organized robot swarms is relatively new, one recent example is the work in [Primiero et al., 2018] where a similar, non-spatial, defence mechanism was designed for the case where dissemination time was symmetric.

Our study is performed using simplified multi-agent simulations and validated on an experiment involving real robots (in this case, Kilobot robots [Rubenstein et al., 2012]).

The remaining of the paper is organized as follows. In Section 2, we define more formally the problem and the methodology used to model it; in Section 3, we present the experimental setup of both simulations and real robot experiment; in Section 4, we discuss the results and the validation with the real robots; in Section 5 we discuss the findings in the light of a larger picture.

Table 1: Experiment Parameters

Notation	Values	Description
N	$[100, 250, 500, 750, 1000]$.	Swarm Population, total number of robots.
ρ_{RED}	$[1.0, 2.5, 3.75, 5.0, 6.25, 7.5, 8.75, 10]$	RED Dissemination Factor.
ρ_{BLUE}	$[1.0]$	BLUE Dissemination Factor.
-	["Voter Model","Majority Rule"]	Voting methods.
k	$[3, 5, 7]$	Minimum number of agents that participate in the voting when usi

2 PROBLEM DEFINITION AND METHOD

We consider a collective decision making-process in a swarm of N agents modeled as the discrete best-of-n [Valentini et al., 2017]. We consider the case $n = 2$, and we label the two options as RED and BLUE. The two options are associated to different dissemination times: the RED option is the *attacker* option and has a longer dissemination time than the BLUE option, the *defender* option.

The dissemination times above are exponentially distributed and each (BLUE or RED) proportional to a parameter that we call *dissemination factor*. Only the ratio between the two dissemination factors play a role. To keep the observation simple, the dissemination factor of BLUE has been fixed to the value 1. Only the RED dissemination factor ρ_{RED} is varied, using values greater or equal to 1. Half of the population is initialized with RED opinion and the other half with BLUE opinion. Agents with RED opinion have dissemination time proportional to RED option value, and those with BLUE opinion will disseminate proportional to BLUE option value. The agents' location are initially randomly distributed.

The agents with the RED opinion implement a random walk and always move freely in an arena with closed bounds and no periodic boundaries. When they do not implement any strategy (here referred to as *No Strategy*), the BLUE agents perform random walk exactly like the agents with the RED option. But, when they implement our novel defence strategy (referred to as *Blue-sticky*), they remain in their initial position. If a RED robot changes opinion after the decision making mechanism, it becomes BLUE and stops in its last position. Within the simulations, collision checks are not implemented and individuals may freely collide or overlap with each other, an assumption that does not hold in the real robot experiments.

The robot behavior can be modeled as a Finite State Machine in Fig. 1. All agents start in a non-dissemination state (NR or NB, for RED and BLUE respectively) and they remain in this state for an amount of time that is randomly sampled from an exponential distribution with parameter $\tau_{ND} = q = 10$, common to RED and BLUE agents. Then they transition to a dissemination state (DR or DB), in which they promote their opinion for an amount of time sampled from an exponential distribution with parameter proportional to the dissemination factor $\tau_D = q \cdot \rho_i$, where $q = 10$ and $i \in \{RED, BLUE\}$, after which they perform *voting* before transitioning again to non-dissemination mode and the cycle repeats. Since, as explained above, we only consider $\rho_{RED} > \rho_{BLUE} = 1$, the dissemination time for the RED option is on average larger than the dissemination time of the BLUE option. In absence of defence mechanisms,

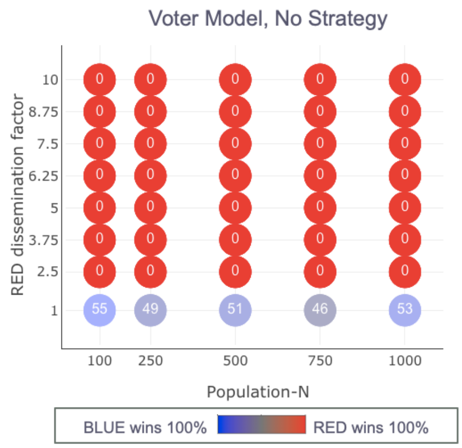

Figure 3: Results with the voter model: No strategy

this is shown to lead to a positive feedback modulation mechanism that makes the system converge to the RED option with higher probability compared to the BLUE option [Valentini et al., 2016]. The role of the parameter q is to rescale dissemination and non-dissemination times in a way to allow the agents to spend enough time in the two states so that they are sufficiently well mixed. The specific value of q does matter, and the value chosen in this paper is compatible with rates that were previously evaluted on real robots [Valentini et al., 2016].

During voting, each robot observes the opinion of nearby disseminating agents and uses this information to determine its next opinion. We consider two voting mechanisms: the voter model and the majority rule. In the voter model, agents change their opinion copying the opinion of a random neighbor, while in the majority model instead agents adopt the opinion of the local majority (k random neighboring agents including the focal robot). Agents who are in non-dissemination mode will not be visible, hence their opinion will not be counted during the voting. This state (sometimes referred to as *latent* state [Montes de Oca et al., 2011]) models for example the situation where agents relocate elsewhere in space to assess the quality of the options, or pause the activity of the communication device to save battery.

The simulation runs for a maximum amount of time $T = 1000000$ time steps or terminates early if a stationary consensus state is reached. In this study consensus is always achieved to one of the two options, hence the time limit T was in practice never reached in our experiments. Various values of population size N and dissemination factor ratio $q = \frac{\rho_{RED}}{\rho_{BLUE}} = \rho_{RED}$ are simulated, as reported in Table 1. For each set of parameters, the simulation is repeated 100 times, and we focus our attention to the percentage of the times the consensus to BLUE is achieved.

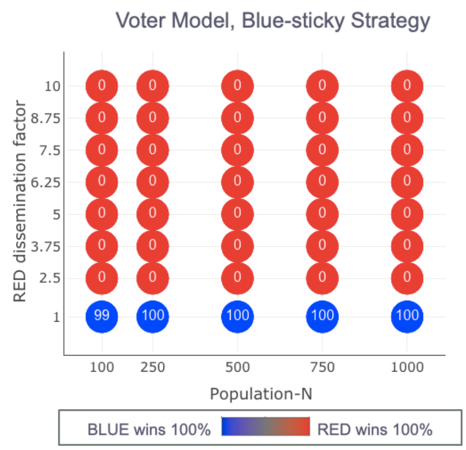

Figure 4: Results with the voter model: Blue-sticky strategy

3 EXPERIMENTAL SETUP

In this section we explain the two setups used for the simulations and for the real robot validation.

3.1 Simulations

The simulations are performed using the Netlogo simulation tool[1]. Individuals sized 1 square-unit each are placed randomly with no overlap in a 2D simulation arena of 100x100 square units as shown in Fig. 2. We considered $N \in [100, 250, 500, 750, 1000]$ as swarm sizes. RED and BLUE opinion are initially assigned in equal proportion to the N agents. The BLUE dissemination factor ρ_{BLUE} is fixed to 1, while the RED dissemination factor is varied within $\rho_{RED} \in [1.0, 2.5, 3.75, 5.0, 6.25, 7.5, 8.75, 10]$. When using the majority rule, we consider the k value $\in [3, 5, 7]$, where k is the number of agents participating in the voting (including the focal robot). For each set of parameters 100 runs have been done.

First, we run baseline experiments without any defence strategy, for all N values and for all dissemination factors considered. Then, we repeat the experiment with the proposed defence strategy, which we call *Blue-sticky* defensive strategy, that has all BLUE agents immobile, again for all values of N and of ρ_{RED}.

3.2 Experiment with real robots

We used Kilobots to run a real robot validation. Kilobots are small-sized and low-cost robots that communicate using Infrared and are also equipped with a light sensor and a RGB LED [Rubenstein et al., 2012]. We placed $N = 20$ robots in a square arena of 50

[1] `https://ccl.northwestern.edu/netlogo/`

Figure 5: Results with the majority model: absence of defender strategy ($k = 3$)

cm by 50 cm, with a relative density of 0.008 $robot/cm^2$, out of which 10 were set to opinion RED (with $\rho_{RED} = 2$) and 10 for opinion BLUE (with $\rho_{BLUE} = 1$). The robots that disseminated RED option were programmed to do the random walk continuously, while the ones supporting BLUE opinion stayed in fixed positions.

The majority rule with $k = 5$ was used. This means they change opinion only when there are a minimum of 4 agents within the sensor range, which covers 10 cm radius. The experiment has been repeated 5 times. The robots start in a non-disseminating state and remain in this state for a time sampled from an exponential distribution with rate equal to rougly $1/3.7\ s^{-1}$ (the actual rate used in the code is 0.009 which produces times in ”kiloticks”, the time unit of the kilobot). Afterwards, the robots transition to the dissemination state, where they disseminate for a time randomly sampled from an exponential distribution with characteristic time proportional to the opinions dissemination factor (the average dissemination time for RED was about 11 s while the average dissemination for blue was 5.55 s, with the actual rate values used in the code being 0.003 for RED and 0.006 for BLUE) . While in the dissemination state, the robots continuously broadcast their opinion as well as their unique 16-bit identier to the neighbours around to ensure their vote is counted only once in a voting cycle. Finally, after disseminating, the robots applies the majority rule and then moves to the non-dissemination state again, and the cycle repeats.

4 RESULTS

In this section we present the results in two parts: results in simulation (Section 4.1) and validation with real robots (Section 4.2).

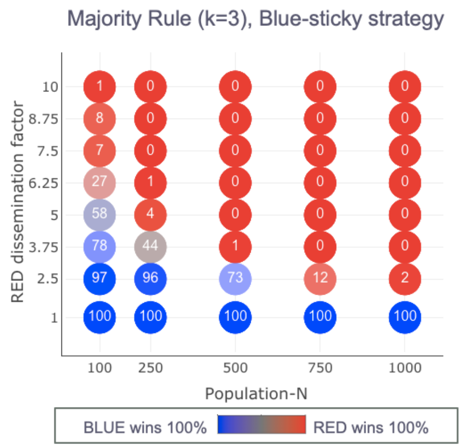

Figure 6: Results with the majority model: defender strategy ($k = 3$)

4.1 Simulation Results

The results of the experiments are plotted on a two dimensional chart. The x-axis represents the population size N, while the y-axis represents the RED dissemination factor, while the BLUE dissemination factor is always set to 1. The white number on the circles represents the percentage of runs where the swarm converged to the BLUE option over 100 runs, using the parameter combination at those coordinates. If BLUE always wins on all the 50 runs, the value is 100. If RED always wins the value is 0. The color shades of red and blue used have the intuitive link to the corresponding option and convergence frequency, with the grey color representing mid-point where BLUE and RED option are having equal number of wins (in terms of runs converged).

As expected, if no strategy is applied, the option with higher dissemination (RED) is winning for both the voter (Fig.2) and the majority voting models (Fig.2). If the two options RED and BLUE have the same dissemination (corresponding to RED factor 1) the consensus state is roughly 50% of the times on RED and 50% of the times on BLUE. This result, called ”symmetry breaking” is well known from the literature. It discloses the tendency to converge to a bistable asymmetric state (in our case consensus to either RED or BLUE), even if starting from a symmetric configuration (in our case, same dissemination factor for both RED and BLUE), due to stochastic fluctuations. The small divergence from 50% observed in the majority rule case (Fig.2) can be explained by stochasticity, due to the fact that the majority rule is less *accurate* as a collective decision making mechanism [Valentini et al., 2016].

If, on the contrary, the sticking strategy is deployed, very different effects can be observed, depending on the voting model. If using the voter model, when the two options have the same dissemination factor, the BLUE option is always winning, independently on the population size N (Fig.2). On the other hand, if the RED dissemination factor is higher than the BLUE one, the RED option is always winning, despite the Blue-sticky

Figure 7: Results with the majority model $k = 5$

strategy (Fig.2). So in this case, the Blue-sticky strategy is effective only in the case the two options have the same dissemination factor, and starts to be ineffective as soon as the dissemination factor of RED option is larger than the BLUE one, at least for the range of considered parameters.

More interestingly, if the majority voting model is implemented, the Blue-sticky strategy is revealing to be more effective to drive the consensus to BLUE option, also for relatively higher dissemination factor values of RED. The results for the three values of k here investigated are reported in Fig.2, 3.1, 3.1. As evident from the figures, in the case with RED dissemination factor equal to 1, the Blue-sticky strategy is effective to make the BLUE agents win, as in the voter model. But the Blue-sticky strategy is still effective also for RED dissemination factor 2.5 and population size $N = 100$. This is true for all the considered k values $[3,5,7]$. Focusing to $N = 100$, when k is increasing, the Blue-sticky strategy is effective even for increasingly higher dissemination factors: Comparing Fig.2, 3.1, 3.1, we can observe that the indifference curve (that is the boundary where in 50% of cases the consensus is achieved to the BLUE option and in the remaining 50% of cases to the RED option) is reached at RED dissemination factor $5, 7.5, > 7.5$ for $k = 3,5,7$ respectively. For larger population sizes N, the Blue-sticky strategy is less resilient to higher values of the RED dissemination factor, with this effect being less pronounced for higher values of k. We believe this is an effect of increased density, where RED agents can successfully infiltrate static Blue-sticky clusters when the density is high, and influence the local majority, an effect that can be attenuated by increasing k which effectively increases the size of the local majority and makes it more robust to RED attacks. We plan to investigate better the effect of density and of k in future work.

We also study how the time to reach consensus is affected by the various parameters. In particular a boxplot representation of time has been used, varying the dissemination factor. The colors of boxplot follows the same conventions of heatmaps.

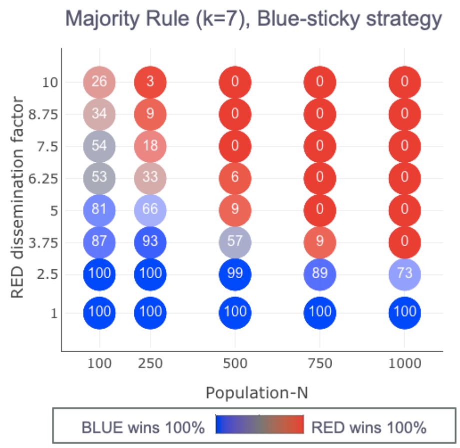

Figure 8: Results with the majority model: $k = 7$.

This study has been done for different population sizes ($N = 100, 250, 500, 750, 1000$) and voting models (voter, majority with $k = 3, 5, 7$). The voter model is very accurate in reaching the consensus, mostly for large population sizes, as already known in literature. However, the consensus is reached only to the RED option, as already discussed; the consensus to BLUE option is only achieved for dissemination factor 1 as described above. Therefore, here we only show the results for majority model [2] with $N = 100, N = 1000$. For small populations, the majority model achieves consensus with shorter times, as also known in literature: majority mechanism is usually faster than voter model, but less accurate [Valentini et al., 2016]. In absence of blue sticky strategy the consensus to BLUE is achieved only with dissemination factor 1 (Fig.9). In majority model, the number of voting neighbors of each agent, i.e. k, is a critical parameter in the decision making mechanism. This parameter plays a crucial role in small systems ($N = 100$), particularly for very large dissemination factors (6 and above), where the RED option wins: comparing Fig.10 ($k = 3$), Fig.4.1 ($k = 5$) and Fig.4.1 ($k = 7$), the larger k, the larger is the variability of time necessary to reach the consensus. This can be easily explained because in small populations and high k values, it is hard to find k neighbors, due to the low density of agents, and agents that do not perceive at least k neighbors do not change opinion. For lower dissemination factors (below 6), where consensus to BLUE is achieved, there is no strong dependency on k value. Here the blue-sticky strategy shows its effectiveness. The blue clusters trigger the consensus and favor the availability of k neighbors, speeding up the majority mechanism.

The other important factor is the population size N, being the consensus times much longer for small systems ($N = 100$), compared with larger systems ($N = 500, 1000$), as evident comparing Fig.10 ($N = 100$, $k = 3$) with Fig.4.1 ($N = 1000$, $k = 3$) and

[2] Voter results are available upon request

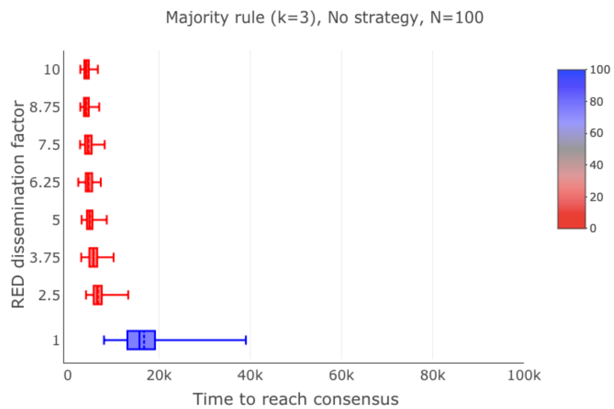

Figure 9: Boxplot plot of consensus time with the majority model: no strategy and $k = 3$

Fig.4.1 ($N = 100$, $k = 7$) with Fig.4.1 ($N = 1000$, $k = 7$) . For larger population sizes the availability of k neighbors is guaranteed by higher density values. Therefore, the majority model is much faster than in the case of small populations.

4.2 Real Robot Experiment

In the real robot runs, the swarm opinion converged completely to Blue on average in 13 minutes and 57 seconds. This test provided evidence of what was observed in the numerical simulations: when the dissemination of RED is higher than the one of BLUE, the BLUE robots can still achieve the consensus using the Blue-sticky strategy. A demonstration video showing one of the runs is available as supplementary material.

5 CONCLUSIONS

In this paper, we study a mechanism to increase the resiliency of a swarm of agents performing collective decision making, subject to attacks represented by the malicious exploitation of the positive feedback modulation. Two options, BLUE and RED, are assumed to have two different dissemination factors, that is two different times of dissemination of their opinions. The BLUE option is characterized by a dissemination factor that is lower than the RED option. Nevertheless, the BLUE option wants to defend its opinion, against the attacks of the RED option. The BLUE option can still win the consensus, when the agents with such opinion use a spatial strategy through which they stay in place and stick the attacker, once it is converted from RED to BLUE. This mechanism is inspired by the defence strategy used by stingless bees, that use some special resin to stick attackers in order to defend themselves. To simulate this behaviour, we divided a swarm in two initially equally populated sets: RED and BLUE. The RED randomly move inside the experimental arena, while the BLUE stick in their original position. In the collective decision making mechanism, a defender (BLUE) is

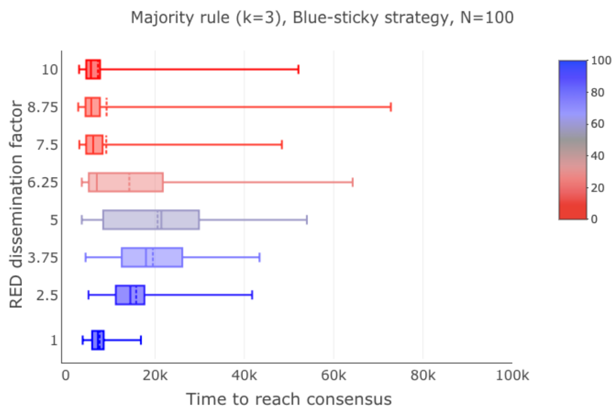

Figure 10: Boxplot plot of consensus time with the majority model: blue strategy and $k = 3$

able to convert the attacker (RED) to change its opinion, sticking it in its last position. In this way the attacker (RED) becomes a defender (BLUE). Through this mechanism, an overall agreement to the defender (BLUE) or attacker (RED) option is always reached. From a design perspective, the final aim is to identify the parameters to obtain the agreement to the defender's opinion. Comparing two different decision making mechanisms, voter and majority models, we found that only the majority rule allows to get consensus with very high probability even when RED is able to disseminate for longer amount of times, but that the voter is able to break the symmetry towards the BLUE option only when the two options are disseminated for an equal amount of time. The majority decision making rule together with the blue-sticky strategy is resilient to attackers having a dissemination factor up to 5 times the dissemination factor of defenders. Moreover, this strategy is effective also in terms of time to reach the consensus: the forming clusters speed up the consensus achievement to BLUE option.

We can conclude that, if agents are attacked by more aggressive agents (with higher dissemination factor), a good strategy for them to win is to stop where they are and progressively form clusters. This study can be particularly relevant for patrolling and surveillance applications. The fact that small systems are more resilient to external attacks, compared with larger systems make this strategy suitable to be applied in real surveillance swarms of agents.

In the next studies, we will investigate the spatial distribution of agents, where agglomeration of blue agents is expected. Finally, we note that the Blue-sticky can be considered a rudimentary aggregation behaviour, as it produces clusters, thus it is in our agenda to study the coupling of collective decision making with other collective behaviours that produce different spatial correlations, such as collective motion or pattern formation.

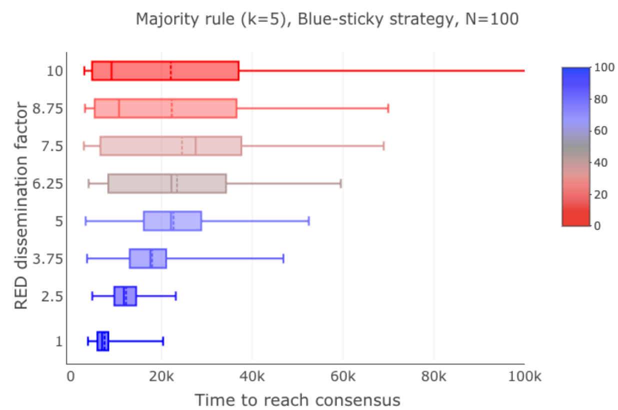

Figure 11: Boxplot plot of consensus time with the majority model: blue strategy and $k = 5$

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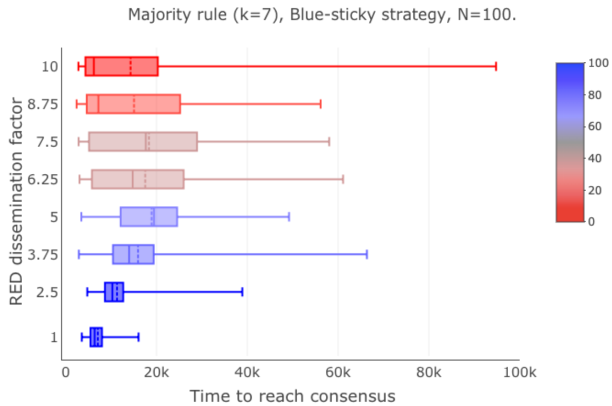

Figure 12: Boxplot plot of consensus time with the majority model: blue strategy and $k = 7$

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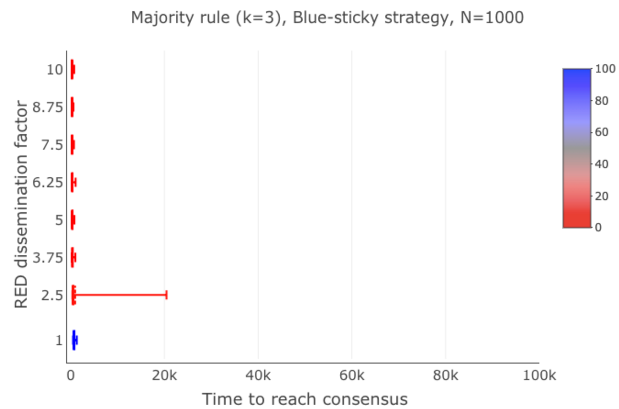

Figure 13: Boxplot plot of consensus time with the majority model, blue strategy and $k = 3$

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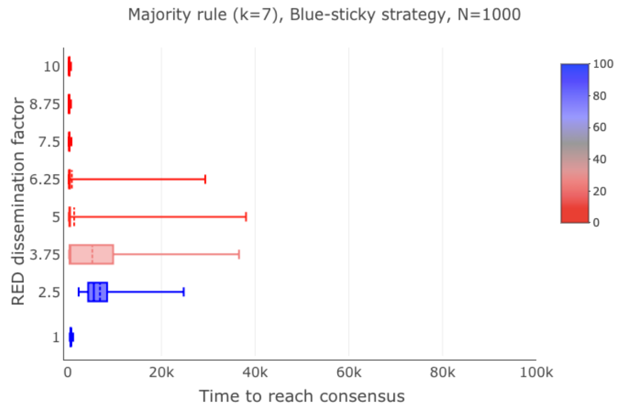

Figure 14: Boxplot plot of consensus time with the majority model, blue strategy and $k = 7$

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Figure 15: Experiment with 20 Kilobots on 50 cm by 50 cm arena